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ABSTRACT

Pennsylvania's Educational Quality Assessment Program provides each participating school with a building level report in which state percentiles are a prominent part. Multiple matrix sampling was being considered as a technique to reduce testing time. However, there was great concern that the error associated with estimating the school mean might lead to markedly different percentiles than obtained by census testing. Generally favorable results are reported from a post mortem simulation of multiple matrix sampling for a 2 to 6 subtest/subgroup sampling plan involving data obtained from over 30,000 students in 500 elementary schools. (Author/BW)

An Evaluation of a Multiple Matrix Sampling Procedure for a State Assessment Program

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Pennsylvania's Educational Quality Assessment Program provides each participating school with a building level report in which state percentiles are a prominant part. Multiple matrix sampling was being considered as a technique to reduce testing time. However, there was great concern that the error associated with estimating the school mean might lead to markedly different percentiles than obtained by census testing. Reported are generally favorable results from a post mortem simulation of multiple matrix sampling for a 2 to 6 subtest/subgroup sampling plan involving data obtained from over 30,000 students in 500 elementary schools.

An Evaluation of a Multiple Matrix Sampling Procedure for a State Assessment Program

Much of the recent literature on multiple matrix sampling has dealt with theoretical aspects of parameter estimation. Various studies suggest ways to optimize estimation under specified restrictions, but only a few investigations have dealt with practical considerations. When one considers the application of multiple matrix sampling to a situation in which, not one, but a battery of instruments are to be given to students, the problem becomes increasingly complex, especially when the instruments vary in size and where some are cognitive and others affective. This circumstance exists in the Pennsylvania Department of Education's (PDE) assessment program. Since 1969 schools have been assessed on each of 10 state adopted goals (PDE, 1973). When a school underwent assessment, all of the students took each of the 11 or 12 instruments in the battery, a process which required about 4 hours of testing time. During a recent review of the Pennsylvania Educational Quality Assessment (EQA) program, advisory committees recommended an enlargement of content coverage in a number of areas. The suggested changes would require several new instruments as well as an increase in the number of items in various other instruments. The inevitable result of instrument expansion is an increase of student testing time to a degree that, in this instance, was judged to be beyond tolerable limits.

Thus, multiple matrix sampling was brought under consideration as a potential time-saving technique. Partitioning instruments into several subtests of non-overlapping items could result in a substantial reduction of testing time while simultaneously permitting an extension of content coverage.

Of immediate concern for planning was the question of the number of subtests to be employed. Given an estimate of the probable number of items

in the final battery and the desire to reduce testing time to approximately two hours, it was determined that about four subtests would be required. A number of people voiced concern over the amount of error that would be introduced by the procedure. For a given number of subtests, the amount of error in estimating a school mean might be well within tolerable limits for one test but beyond the acceptable range for another. An additional concern revolves around the question of how much error is tolerable. A determination of tolerable error will also influence a decision regarding the number of subtests to have. How can the question be translated into terms meaningful to administrators of assessment programs?

In the EQA program, mean test scores are produced for each building. Included in a school report (PDE, 1974) is the state percentile rank attained by that school on each test. Hence, a major concern was whether a school mean, as estimated by multiple matrix sampling, would place the school at approximately the same percentile as the mean score attained by census testing. Thus, one approach to evaluating the effect of matrix sampling is in terms of the difference in percentile rank achieved by these two methods. For example, suppose an uncomfortably high percentage of schools deviated from their "true" placement by more than, say, 10 percentile points when multiple matrix sampling was applied. EQA staff was concerned that such a circumstance would greatly hinder the believability of the assessment report by school people who are accustomed to receiving information based on census testing. This concern is especially acute in low scoring schools where there is a greater tendency for a worried administration to attempt to discredit the report by claiming the results contain too much error to be trustworthy. To get a picture of the amount of error the EQA program would have to live with under various sampling plans, a simulation of multiple matrix sampling was conducted in the Fall of 1975.

Method

Instruments

Instruments in the EQA package range from 28 items to 63 items, depending on grade level. Consideration was given to multiple matrix sampling plans with two to six subtests equally balanced with respect to items from each instrument. The instruments selected for the simulation included both cognitive and non-cognitive measures and are more fully described in the EQA technical manual (PDE, 1975). A 40 item self esteem scale having a four choice Likert format represented non-cognitive area. This scale, similar to the Coopersmith (1967) Self Esteem Inventory, is internally consistent (Coefficient Alpha of .88, N = 3400) with item means ranging from 1.29 to 2.30 and an average item mean of 1.72 where item values range from 0 to 3. Cognitive measures included a 30 item verbal analogies test and a 60 item composite achievement consisting of verbal analogies and mathematics reasoning. Internal consistency reliability estimates for verbal analogies was .83 and mathematics reasoning .79. Difficulty level ranged from .19 to .95 with an average of .60 for verbal analogies and .16 to .95 with an average of .63 for composite achievement. These instruments were selected for the simulation exercise since they were each capable of subdivisions into at least three matrix sampling plans. For example, a 40 item scale may be divided into two 20 item subtests, four 10 item subtests and five 8 item subtests. Using instruments with 30, 40 and 60 items for the simulation exercise should provide a reasonable picture of what to expect in practice since they represent the range of instrument sizes found in the battery. Since the most severe estimation problems occur for elementary schools, which generally have much smaller enrollments than secondary schools, the 5th grade data base was chosen.

Procedure

The procedure followed that of the typical post mortem simulation in which data, originally collected by having students answer all the items, is later acted upon as if the students had taken different subsets of items. In multiple matrix sampling, a universe of K items has been partitioned into T subtests of k items. The population of N students is randomly divided into T subgroups of n students. Each subgroup of students takes a different subtest. An estimate of the parameter of interest is computed for each subgroup and a linear combination is obtained for the population estimate. In the current situation we are interested in estimating the mean test score for a school for hypothetical 2-subtest/2-subgroup to 6-subtest/6-subgroup cases. Since data have already been collected via census testing each student has responded to all items. Random sampling of items into subtests is frequently used in Monte Carlo studies; however, the literature contains some suggestions regarding the advisability of assigning items according to a stratification based on item characteristics such as difficulty level. The present study attempted to create an optimal item assignment and an adverse assignment condition. Using item analysis information from a data base of about 3400 cases, the items were first rank ordered with respect to item mean. A <u>matched</u> condition was created by alternately assigning items from the ordered list to a subscale in the two subscale case. In the five subscale case, items ranked 1, 6, 11, ...were assigned to the first subscale, items ranked 2, 7, 12, ...to the second subscale, etc. This procedure was followed in order to make the subscales as comparable as possible. A dissimilar or <u>ranked</u> condition was produced by assigning items to subtests so as to maximize the difference between subtests in terms of average item mean. For example, under a two subtest situation the "lowest" half of the items

were assigned to one subtest and the "largest" half to the other subtest. Likewise, in the five subscale case, the "lowest" fifth of the items were assigned to the first subscale, the next fifth to the second subscale, and so on.

Identified in Table 1 are the matrix sampling conditions investigated in the present study. The table also shows the average item mean for those items comprising each subtest under both the matched and ranked conditions.

Place Table 1 About Here

The assignment of students was accomplished by systematic sampling procedures. First of all, the order in which student data records appear on the 1975 grade 5 assessment data tape is essentially random. All records for the students within a particular school were located together. Student data for 500 elementary schools (approximately 31,000 students) were contained on the tape. In the two subtest/two-subgroup condition, students were assigned alternately to the first, then the second subgroup. In the five-subtest/five-subgroup case, students were similarly assigned. This procedure approximates the method that EQA would use in practice. That is, in testing a large group of students "subtest packages" would be prepared and interspersed. For example, if there were two subtests, every other student would receive the same subtest package.

A FORTRAN IV computer program was written by the author to produce, for each school building, an estimated mean developed from a composite of the separate subtest means.

An estimate of a school mean, $\hat{X}$ via multiple matrix sampling is given by:

$$\hat{X} = \sum_{t=1}^{T} \bar{X} \cdots$$

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The symbol $\bar{X}_t$ is the mean score for a given subtest which is found by:

$$\bar{X}_t = \sum_{i=1}^{n} X_{t_i}/n$$

In the above formula, n refers to the number of students taking the subtest and X_{t_i} is the summated score for the ith examinee on the tth subtest,

$$X_{t_i} = \sum_{j=1}^{k} X_j$$

where, k = number of items in the subscale

and, X_j = an item score

An actual school mean was also computed in the conventional manner. These results were printed, then the next school's data was read and the process repeated. After results were printed for all 500 elementary schools, the program computed the standard error of estimate by averaging the sum of the squared deviations of the estimated school mean from the actual school mean. Also, computed was the correlation between the actual and estimated school mean. Percentile ranks, derived from the grade 5 statewide norm sample, were assigned to each school's estimated and actual mean scale norm score. The frequency and percent of schools having a certain sized discrepancy and percent of schools having a certain sized discrepancy between the two percentile ranks were computed and printed.

Results and Discussion

Comparisons among the conditions investigated were made on the basis of the correlation between actual and estimated school means, standard error and frequency of deviant percentiles.

Displayed in Table 2 are the correlations between actual and estimated school means for each case investigated. Note the gradual decrease in the magnitude of r as the number of subtests increases. Such a result should be anticipated since the error in estimating a school mean will also increase as a fixed number of items is partitioned into more and more subtests. Without exception the r observed for the matched condition is higher in magnitude than r obtained in the ranked condition. The effect is highly consistent although the difference between r's for the matched and ranked condition is not statistically significant in any of the cases.

Place Table 2 about here

Summarized in Tables 3 through 7 are the standard errors and proportion of schools with given percentile differences for matched and ranked conditions. Data is presented for four categories of grade enrollment as well as the total sample of 500 schools. Table 3 contains results on both conditions for self esteem. Because of the greater number of subtests examined for verbal and composite achievement, results for matched and ranked conditions are given in separate tables.

Place Tables 3-7 about here

One can readily note the increase in estimation error resulting from an increase in the number of subtests. It should be remembered that with each increase in the number of subtests there was a corresponding decrease in the

number of items forming a subtest, hence, a decrease in the number of observations comprising the estimated school mean. Also consistent with statistical expectation is the increase in estimation error associated with a decrease in grade enrollment. The latter effect is a significant one for a state assessment program when one considers the large number of schools with small grade enrollments. In the present sample about 125 of the 500 elementary schools (20 per cent) have a 5th grade enrollment of 30 or less. Thus it is imperative to examine the estimated amount of error for schools of various grade enrollments as well for the total sample.

Returning to a comparison of the matched and ranked items assignment conditions, a perusal of the 12 parallel cases exhibited in Tables 3 - 7 reveals a highly consistent picture of smaller error estimates for the matched condition. As one should expect, casting the data in the form of percentile differences leads to the same pattern of superiority in favor of the matched condition. In summary, the matched condition demonstrated a more favorable profile (higher correlations, smaller standard error and lower frequency of deviant percentiles) than the ranked or dissimilar condition for all cases studied. Support was thereby obtained for establishing subtests that are very similar to one another in terms of average item mean. However, it should be remembered that the effect displayed is one of extremes. The ranked condition may be regarded as the least desirable method for allocating items to subtests. Such a condition is unlikely to occur in practice, but the results do help to define an "upper bound" of error. In the absence of stable item analysis information to first stratify items according to mean score or other statistical properties, one would allocate items by random assignment. Simple random assignment should assure a similar composition of items across subtests, especially when the number of items per subtest

is large, and thereby achieve an essentially matched condition.

While one can readily observe that the standard error increased with an increase in subtests and with a decrease in grade enrollment, how does one judge the amount of tolerable error? In retrospect it might have been better to score the achievement tests in terms of proportion of correct answers rather than number correct. This would standardize reporting across tests. Establishing an acceptable range of error might be accomplished more readily since the metric itself is easily understood. In the case of a non-cognitive scale with a Likert type format, a summated score is more obscure, unless the items are dichotomously scored. Then scoring could take the form of proportion of items answered in the positive direction. To be understood by non-statistically oriented individuals who must make policy decisions regarding a large scale assessment program, it seemed reasonable to translate the data into terms which might be more readily apprehended. Considering the results in terms of the difference in percentile rank attained by the school's actual and estimated mean, was an effort at getting a picture of the simulation in a context familiar to the assessment program's policy makers.

Consider the matched condition results shown in Table 6 for composite achievement. Suppose that a percentile difference of $\pm$ 0 to 10 points represented a "tolerable" range of error. Looking first at the matched condition for five subtests and combining the 0 - 5 and 6 - 10 categories, we find that 69 percent of the schools having 30 or fewer 5th grade students fall in the acceptable error range while 84 percent of the schools with 31 - 60 students reach the acceptable range. With only two subtests, one could expect 96 percent and 99 percent reaching the tolerable range for these two enrollment categories. Compare these results with those obtained on an

instrument containing half as many items. In Table 4 only 55 percent and 76 percent of the schools in the lower two enrollment categories reach the acceptable range when there are five subtests. With two subtests the situation improved to 85 percent and 96 percent.

In evaluating the results for the Pennsylvania program, there was a concern that approximately 90 percent of the schools achieve estimated means deviating by no more than 10 percentile points. Thus, a tentative decision was made to develop a grade 5 test package having two or possibly three subtests per goal area. Even two or three subtests will yield a substantial savings in test taking time.

This study would appear to lend confidence to the use of multiple matrix sampling techniques in large scale assessment programs when the major thrust is providing school building information as a service function as opposed to simply obtaining statewide aggregates for presentation to the state legislature. When an assessment program relies at least partially on a norm referenced model of reporting data, the estimates of a school mean must have a sufficiently low error so results are acceptable to school people. Any large scale testing program considering multiple matrix sampling would find simulation profitable in formulating guidelines for tailoring procedures to the specific parameters of the program such as number of test items, type of reporting unit and a host of other considerations.

References

1. Pennsylvania Department of Education. Educational Quality Assessment in Pennsylvania: The First Six Years. Harrisburg, Pennsylvania, 1973.

2. Pennsylvania Department of Education. Educational Quality Assessment Manual for Interpreting Elementary School Reports. Harrisburg, Pennsylvania, 1974.

3. Pennsylvania Department of Education. Getting Inside the EQA Inventory: Grade 5. Harrisburg, Pennsylvania, 1975.

4. Coopersmith, S. The Antecedents of Self-Esteem. San Francisco, California: Freeman, 1967.

Table 1

Mean Values for Items Comprising Each Form
Examined in the Matched and Ranked Conditions

Subtests		Self Esteem Matched	Self Esteem Ranked	Verbal Achievement Matched	Verbal Achievement Ranked	Composite Achievement Matched	Composite Achievement Ranked
2	1	1.74	1.52	0.59	0.44	0.61	0.44
	2	1.71	1.93	0.60	0.76	0.61	0.79
3	1			0.59	0.39	0.62	0.39
	2			0.60	0.60	0.61	0.62
	3			0.61	0.81	0.61	0.84
4	1	1.72	1.41			0.61	0.36
	2	1.73	1.63			0.61	0.53
	3	1.73	1.80			0.62	0.71
	4	1.72	2.05			0.62	0.87
5	1	1.74	1.39	0.59	0.35	0.61	0.34
	2	1.70	1.57	0.61	0.46	0.62	0.48
	3	1.74	1.73	0.61	0.61	0.62	0.62
	4	1.72	1.84	0.60	0.73	0.62	0.75
	5	1.73	2.09	0.59	0.85	0.61	0.88
6	1			0.58	0.34	0.61	0.32
	2			0.61	0.44	0.61	0.46
	3			0.60	0.52	0.61	0.56
	4			0.61	0.68	0.62	0.68
	5			0.60	0.75	0.61	0.78
	6			0.60	0.86	0.62	0.89

Table 2

Correlations Between Actual and Estimated School Means for Each Case Investigated

Subtests	Self Esteem Matched	Self Esteem Ranked	Verbal Achievement Matched	Verbal Achievement Ranked	Composite Achievement Matched	Composite Achievement Ranked
2	.986	.968	.985	.978	.989	.983
3			.973	.960	.980	.972
4	.941	.934			.973	.961
5	.937	.898	.938	.920	.956	.948
6			.928	.914	.943	.935

Table 4

Multiple Matrix Sampling Simulation
Matched Conditions, Verbal Achievement, 30 Items

Number of Subtests	Grade Enroll-ment	N	Std. Error	Proportion of Schools With Given Percentile Differences 0-5	6-10	11-15	16-20	21+
2	1-30	124	0.413	.65	.20	.10	.02	.02
	31-60	173	0.347	.74	.21	.05	.00	.00
	61-90	129	0.257	.84	.14	.02	.00	.00
	91-	74	0.186	.93	.07	.00	.00	.00
	TOTAL	500	0.326	.77	.17	.04	.01	.01
3	1-30	124	0.549	.58	.25	.08	.05	.03
	31-60	173	0.456	.68	.19	.08	.03	.02
	61-90	129	0.392	.68	.22	.08	.01	.00
	91-	74	0.255	.82	.12	.05	.00	.00
	TOTAL	500	0.444	.68	.20	.08	.02	.02
5	1-30	124	1.045	.37	.18	.16	.12	.16
	31-60	173	0.626	.51	.25	.13	.07	.04
	61-90	129	0.507	.63	.21	.09	.04	.03
	91-	74	0.378	.64	.23	.12	.01	.00
	TOTAL	500	0.701	.53	.22	.13	.07	.06
6	1-30	124	1.007	.45	.18	.05	.08	.24
	31-60	173	0.742	.43	.25	.14	.10	.08
	61-90	129	0.594	.59	.18	.14	.04	.05
	91-	74	0.406	.64	.24	.12	.00	.00
	TOTAL	500	0.750	.51	.21	.12	.07	.10

Table 3

Multiple Matrix Sampling Simulation, Matched and Ranked Conditions, Self Esteem, 40 Items

Number of Subtests	Grade Enroll-ment	N	Std. Error	Proportion of Schools With Given Percentile Differences				
				0-5	6-10	11-15	16-20	21+
2	1-30	125	0.966	.66	.25	.07	.02	.00
	31-60	174	0.839	.73	.15	.09	.03	.01
Matched	61-90	128	0.584	.85	.10	.03	.02	.00
	91-	73	0.438	.89	.05	.05	.00	.00
	TOTAL	500	0.776	.77	.15	.06	.02	.00
	1-30	125	1.517	.49	.19	.20	.02	.10
	31-60	174	1.092	.52	.22	.13	.07	.05
Ranked	61-90	128	0.808	.51	.27	.13	.05	.04
	91-	73	0.777	.48	.25	.21	.07	.00
	TOTAL	500	1.117	.50	.23	.16	.05	.04
4	1-30	125	2.249	.46	.16	.15	.07	.16
	31-60	174	1.493	.51	.25	.09	.11	.05
Matched	61-90	128	1.182	.57	.23	.13	.05	.01
	91-	73	0.736	.64	.25	.11	.00	.00
	TOTAL	500	1.570	.53	.22	.12	.07	.06
	1-30	125	2.259	.41	.19	.16	.06	.18
	31-60	174	1.651	.41	.24	.14	.08	.12
Ranked	61-90	128	1.156	.49	.23	.16	.07	.05
	91-	73	1.084	.45	.33	.14	.04	.04
	TOTAL	500	1.659	.44	.24	.15	.07	.10
5	1-30	125	2.382	.49	.10	.13	.10	.18
	31-60	174	1.518	.51	.25	.09	.09	.06
Matched	61-90	128	1.149	.55	.23	.13	.08	.01
	91-	73	0.830	.67	.16	.11	.04	.01
	TOTAL	500	1.627	.54	.20	.11	.08	.07
	1-30	125	2.931	.36	.22	.10	.07	.24
	31-60	174	2.031	.38	.17	.17	.11	.17
Ranked	61-90	128	1.414	.51	.2[illegible]	.13	.05	.10
	91-	73	1.118	.42	.26	.19	.04	.08
	TOTAL	500	2.064	.41	.21	.15	.08	.16

Table 5

Multiple Matrix Sampling Simulation
Ranked Conditions, Verbal Achievement, 30 Items

Number of Subtests	Grade Enroll-ment	N	Std. Error	Proportion of Schools With Given Percentile Differences 0-5	6-10	11-15	16-20	21+
2	1-30	124	0.532	.55	.27	.10	.05	.03
	31-60	173	0.403	.68	.22	.08	.02	.00
	61-90	129	0.318	.77	.20	.03	.00	.00
	91-	74	0.265	.77	.20	.03	.00	.00
	TOTAL	500	0.403	.68	.22	.06	.02	.01
3	1-30	124	0.735	.50	.24	.10	.07	.09
	31-60	173	0.545	.61	.22	.10	.04	.03
	61-90	129	0.430	.67	.24	.07	.02	.00
	91-	74	0.360	.66	.19	.14	.01	.00
	TOTAL	500	0.551	.60	.23	.10	.04	.03
5	1-30	124	1.093	.34	.24	.13	.10	.19
	31-60	173	0.737	.43	.28	.14	.06	.09
	61-90	129	0.541	.57	.20	.13	.06	.03
	91-	74	0.476	.58	.23	.12	.05	.01
	TOTAL	500	0.770	.47	.24	.13	.07	.09
6	1-30	124	1.099	.35	.29	.10	.08	.18
	31-60	173	0.808	.47	.24	.10	.10	.09
	61-90	129	0.643	.46	.26	.13	.07	.08
	91-	74	0.574	.59	.22	.12	.04	.03
	TOTAL	500	0.824	.46	.25	.11	.08	.10

Table 6

Multiple Matrix Sampling Simulation
Matched Conditions, Composite Achievement, 60 Items

Number of Subtests	Grade Enroll-ment	N	Std. Error	Proportion of Schools With Given Percentile Differences 0-5	6-10	11-15	16-20	21+
2	1-30	124	0.661	.73	.23	.04	.01	.00
	31-60	173	0.457	.85	.14	.01	.00	.00
	61-90	128	0.353	.95	.05	.00	.00	.00
	91-	75	0.309	.99	.01	.00	.00	.00
	TOTAL	500	0.475	.87	.12	.01	.00	.00
3	1-30	124	0.831	.66	.22	.07	.04	.01
	31-60	173	0.689	.71	.19	.09	.01	.00
	61-90	128	0.496	.80	.16	.03	.00	.00
	91-	75	0.361	.91	.09	.00	.00	.00
	TOTAL	500	0.648	.75	.18	.06	.01	.00
4	1-30	124	0.992	.56	.26	.10	.02	.05
	31-60	173	0.758	.69	.20	.08	.03	.00
	61-90	128	0.656	.78	.15	.06	.00	.01
	91-	75	0.465	.83	.17	.00	.00	.00
	TOTAL	500	0.764	.70	.20	.07	.02	.01
5	1-30	124	1.297	.48	.21	.14	.10	.07
	31-60	173	1.016	.57	.27	.08	.04	.04
	61-90	128	0.739	.70	.19	.07	.03	.01
	91-	75	0.642	.71	.20	.08	.01	.00
	TOTAL	500	0.987	.60	.22	.09	.05	.03
6	1-30	124	1.680	.34	.28	.17	.09	.12
	31-60	173	1.021	.56	.24	.10	.08	.01
	61-90	128	0.830	.73	.14	.09	.03	.01
	91-	75	0.594	.69	.25	.05	.00	.00
	TOTAL	500	1.137	.57	.23	.11	.06	.04

Table 7

Multiple Matrix Sampling Simulation
Ranked Conditions, Composite Achievement, 60 Items

Number of Subtests	Grade Enroll-ment	N	Std. Error	Proportion of Schools With Given Percentile Differences				
				0-5	6-10	11-15	16-20	21+
2	1-30	124	0.851	.61	.27	.08	.02	.01
	31-60	173	0.594	.79	.18	.03	.00	.00
	61-90	128	0.448	.87	.10	.03	.00	.00
	91-	75	0.384	.92	.08	.00	.00	.00
	TOTAL	500	0.614	.78	.17	.04	.01	.00
3	1-30	124	1.075	.50	.31	.12	.02	.05
	31-60	173	0.804	.70	.21	.06	.03	.01
	61-90	128	0.614	.79	.17	.03	.01	.00
	91-	75	0.554	.73	.23	.03	.01	.00
	TOTAL	500	0.810	.68	.23	.06	.02	.01
4	1-30	124	1.251	.46	.26	.12	.10	.06
	31-60	173	0.947	.55	.29	.09	.05	.02
	61-90	128	0.664	.79	.14	.05	.02	.00
	91-	75	0.601	.80	.16	.01	.03	.00
	TOTAL	500	0.929	.63	.23	.08	.05	.02
5	1-30	124	1.495	.41	.26	.18	.04	.11
	31-60	173	1.044	.58	.21	.09	.07	.05
	61-90	128	0.801	.66	.20	.10	.03	.01
	91-	75	0.670	.73	.21	.04	.00	.01
	TOTAL	500	1.079	.58	.22	.11	.04	.05
6	1-30	124	1.598	.45	.20	.15	.10	.10
	31-60	173	1.322	.54	.18	.13	.06	.08
	61-90	128	0.808	.69	.19	.07	.04	.02
	91-	75	0.719	.63	.29	.07	.01	.00
	TOTAL	500	1.217	.57	.20	.11	.06	.06